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DESIGN FOR RELIABILITY – RELIABILITY PREDICTION & CORRELATION STUDY USING TEST RESULTS AND FIELD FEEDBACK

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ABSTRACT

In the competitive market, Quality and Reliability are playing a vital role. Reliability is a measure of quality, which is a key characteristic at each stage of the product starting from Design through Manufacturing, Assembly, Delivery & Usage in the field. Reliability is differentiated from quality by being particularly concerned with time [1]. Reliability gives the data about how long the product will work with specified quality. Reliability is defined as the probability that an item will perform a required function for a given period of time when used under stated operating conditions [1]. The reliability stresses on four elements namely [1]; Probability, Intended function, Time, and operating conditions. Reliability / Design life of the product could not be predicted accurately using Lab test failures unless it is correlated with Field conditions. This gap can potentially result in increased Cost of Poor Quality (COPQ) [2], increase in warranty returns & most importantly Customer dissatisfaction. On the other hand, over designing due to inaccurate reliability / Design life predicted results in the unnecessary increase in product cost, reducing the profit. The conventional way of product development is, designing & developing the product as per requirements & then validation of design by physical testing. The testing process involves, subjecting the samples to various test conditions like vibration test, corrosion test, etc., for pre-defined test duration as per national & international standards. If the sample passes all the required tests, then the product will be launched. A major drawback in this system is tested standards do not always reveal the field failures. Unless we know the correlation between test conditions & field conditions, field failures cannot be predicted or eliminated. This paper estimates the reliability of carburetor from its lab test and field failures. A warranty period of one year is accounted for the calculation of reliability. This means product reliability at the end of one year is predicted and the same is compared with the reliability calculated from warranty / field failures, to check if any Over design exists or opportunity exists to improve the reliability of the product. A two-wheeler carburetor is selected for this study & the methodology can be horizontally deployed to any product

KEYWORDS: Design for Reliability, Cost of Poor Quality, Customer Satisfaction & Warranty Failures

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1. INTRODUCTION

The reliability of the system depends on the arrangement of components in the system. The reliability of the product directly influences its total cost. The total cost of the product consists of, Before shipment and After shipment costs. "Before shipment costs" includes but not limited to Research, Engineering, Development, Manufacturing, Quality check, etc., "After shipment costs include but not limited to Transportation, Installation,

Startup, Warranty and Goodwill costs [1].

The higher reliability of the product increases the before shipment costs and reduces the after shipment costs. The sum of these two costs and adding profit will give the producer's selling price. The influence of the reliability on the after and before shipment costs and also on the total cost is shown in Figure 1 [3]

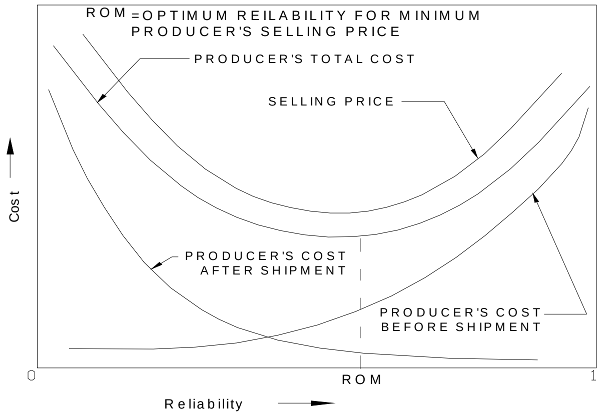

Figure 1: Reliability of the Product at Various Cost Level [3]

The reliability of the system depends on the reliability of components; their arrangement in the system and the availability of similar or different redundant components. Designer shall consider these parameters to achieve the higher reliability at a lower cost. Reliability / Design life of the product could not be predicted accurately with the existing system since the Reliability predicted from lab test failures does not necessarily represent field failures. The typical manufacturer does not really know how satisfactorily its products are functioning. This is usually due to a lack of a reliability-wise viable failure reporting system. It is important to have a useful analysis, interpretation, and feedback system in all company areas that deal with the product from its birth to its death. On the other hand, if the products functioning truly satisfactorily, it might be because they are unnecessarily over-designed; hence they are not designed optimally. Consequently, the products may be costing more than necessary and lowering profits. Products are becoming a more complex yearly, with the addition of more components and features to match competitors' products. This means that products with currently acceptable reliabilities need to be monitored constantly as the addition of features and components may degrade the product's overall reliability.

1.1 Situations that Demand Reliability Prediction

The following points are the critical situation, which demands reliability prediction of the product;

- In the current situation, if the product reliability is not up to the expectation of customer / end user, the organization will lose its business. The first step in improving the reliability is calculating present status.
- Without knowing the product reliability, field failures cannot be predicted & eliminated
- Effective cost optimization is not possible if the product reliability is not known. That is product reliability metrics are useful inputs for design optimization [2]
- Liability for the unreliable product is very high in the global market.
- High cost to service / replace warranty claims

In many ways, product reliability prediction can be used as a tool for Cost reduction, Design optimization and to satisfy customer expectations. Also, it indirectly reduces the development lead-time of products, which gives an advantage for the organization in the competitive market. To be precise, if the organization ensures product reliability, it needs not to spend time for different iterations of the development cycle.

2. METHODOLOGY AND NATURE OF DATA NEEDED

Reliability prediction & Life data analysis involves extended use of failure data. Though life prediction is possible with non-failed samples data, results won't be accurate. The following failure data are useful to predict the reliability of component / product [3]

- Complete data
- Left-censored data
- Right-censored data or suspended data
- Interval-censored data

Amongst the above list, complete data would be most preferable. But practically it is not feasible to capture complete data. For example, consider the case of carburetor under vibration test. To capture the exact failure duration of performance characteristics, we can go for a data logger connected to a digital flow sensor, so that it will continuously monitor the floe characteristics. But data logger cannot monitor the mechanical failures like mounting clamp cut, nozzle dislodges, body crack, etc. Hence considering the above practical difficulties "Suspended data with interval censoring" is selected for life data analysis of carburetor assembly.

For reliability prediction following are the major contents of data required [3]

- Failure duration (In intervals)
- Number of samples failed
- Type of failure (For Root Cause Analysis)
- Number of samples with failure-free operation
- Duration of suspension

2.1 Various Sources of Data

Reliability analysis can be carried out using the failure data of the product. Following are the major sources of failure data' [3]

- Test Bench Failures of products
- Warranty / Field Failures
- Accelerated life test failures
- Reference sources of component failures (Mainly for electronic components)
- Component failure data from suppliers.

From the above sources of failure data, this paper concentrates on the first two sources

2.1.1 Failure Data from Bench Tests

The product shall be subjected to different test conditions as per national, international & customer standards. All those test conditions can be categorized into four major categories namely;

- Electrical tests – Since its a mechanical product, this is not applicable in the study
- Environmental tests like High temperature, Low temperature, Thermal shock, and Corrosion resistance
- Dynamic tests like Sine Vibration, Shock test
- Endurance tests like Constant speed operation, Cyclic operation
- Field simulation tests like Random vibration, Road condition simulator

2.1.2 Warranty or Field Failures Data

Product reliability can also be predicted using the warranty / field failure data of the product. This form of data is more accurate than any other. This data can also be used to arrive the correlation between field conditions & test conditions. In quality, perspective organization will only concentrate on the quantity failed within the warranty period, not on the duration covered by each sample before failure. In this category of data source, the following points should be captured to predict the reliability of the product.

- Quantity failed
- Duration covered by each product before failure
- Manufacturing month of the failed product & Total quantity supplied during that month
- Type of failure
- Applicability of warranty claim

Last two data points can be utilized for Root cause analysis & countermeasures [4]

3.0 DATA COLLECTION

3.1 Potential Failure Mapping

The product is studied and critical components identified are listed in Table 1. This table also explains about the applicability of various tests by which the component is likely to fail & is identified by a "*". Blank cells state that the particular test doesn't have any impact on the performance of the component. This data is used to arrive the test specification & also to find out the comparatively severe test condition, which can reveal the field failures within a short span of time. [4] [5]

Table 1: Various Tests and Applicability of Components

Component Name	Nature of tests									
	Corrosion Resistance	High Temperature	Low Temperature	Humidity	Thermal shock	Vibration - Sine	Vibration - Random	Bump	Leak test	Operation Durability
Outer body		*	*	*		*	*	*		
Main jet & Pilot jet						*	*		*	*
Pilot screw						*	*	*	*	*
Diaphragm		*	*	*	*		*		*	*
Piston valve		*		*			*	*		
Butterfly valve			*			*	*	*		
Diaphragm spring	*			*		*	*			*
Mounting clamp, Spring	*			*		*	*	*		
Air valve hose		*	*		*				*	
O ring – Main jet		*	*		*		*		*	
Float, Plunger				*	*	*	*	*		*
Float spring	*			*			*	*		*
Jet needle spring	*			*			*	*		*
Air valve					*			*	*	
Chock lever	*		*	*		*	*	*		
Float pin, Drain screw				*		*	*	*		*

* : Chances of failure exists.

Considering the above failure data & arrangement of components, the product is classified into following five categories; Sub-system A, B, C, D & E [5]

3.2 Data from Test Bench Results (Historical Data)

To predict the reliability of product using test bench failures, a product needs to undergo different tests as per national / international / customer specification. Once we have the failure data out of those tests, we can predict the reliability product for each test. But the test duration needs to be converted to kilometers then only the test bench reliability & field reliability can easily be compared. To arrive the conversion factor for each test, the latest routine validation tests results considered & are tabulated as follows;

Table 2: Test Results from Database

Classi-fication of tests	Nature of test	Test Duration	Inspection interval set	Sample failed / suspended after (Intervals not mentioned)				
				S.No.1	S.No.2	S.No.3	S.No.4	S.No.5
Environmental	Corrosion resistance	50 Hours	5 hrs	55	55	55*	55*	50*
	High temp.	192 hours	20 hours	220*	220 *	220 *	200	200
	Low temperature	192 hours	20 hours	220*	220 *	220 *	220 *	220 *
	Humidity	192 hours	20 hours	220*	220 *	220 *	220	220
	Thermal shock	100 cycles	10 cycles	110*	110*	110*	110*	110*
Dynamic	Vibration - Sine	8 hours	1 hour	9*	9	9*	7	9
	Vibration – Random	60 hours	5 hours	55	50	60	60	45
	Bump	1000 bumps	100 bumps	1100*	1100*	1100*	1100*	1100*
Endurance	Leak test	100 cycles	10 cycles	110*	110*	110*	110*	110*
	Operational durability	100,000 cycles	10,000 cycles	110,000*	110,000*	110,000*	110,000*	110,000*

The above specifications have been arrived to ensure product reliability in the field for the period of one year. In simple terms, if the product passes the above test duration, there will not be any field failure for the period of one year, provided all the process variations are taken care-off. Because the organization offers one year warranty for its products. By considering this factor, this test duration is assumed as equivalent to that of one usage of the product in the field. Based on the above failure data, we could observe that dynamic tests are having more impact on product failure & its probability of failure is comparatively more for dynamic tests, especially random vibration. Based on the same, the following matrix is assumed, to quantify Relative risk of failure in each test.

Table 3: Relative Risk of Failure in Difference Tests

Test Description	Relative Risk of Failure (1 = Highest RISK)
Corrosion resistance	0.6
High temperature	0.1
Low temperature	0.1
Humidity	0.3
Thermal shock	0.3
Vibration – Sine	0.8
Vibration – Random	1.0
Bump	0.7
Leak test	0.2
Operational durability test	0.2

3.3 Field Failure Data

To compare the stress level applied to the product in the different test conditions, field failure data of the product have been collected. Since the warranty period of the product is one year, details of the failures received during the last one year have been considered for the analysis. This data can be useful to verify whether the stress level exerted on to the product in the test bench is the same as the product experiences in the field. Following tabular column is the data consolidated from the field failures. Failures within the warranty period are only considered.

Table 4:Field Failure Data of One-Year

		Month of manufacture																							
		Dec '18	Nov '18	Oct '18	Sep '18	Aug '18	Jul '18	Jun '18	May '18	Apr '18	Mar '18	Feb '18	Jan '18	Dec '17	Nov '17	Oct '17	Sep '17	Aug '17	Jul '17	Jun '17	May '17	Apr '17	Mar '17	Feb '17	Jan '17
Qty. Supplied		40,986	62,098	34,098	45,380	39,400	54,925	43,972	42,875	54,878	48,930	43,679	53,295	45,121	62,345	43,968	56,120	38,200	54,925	30,129	57.692	40,400	48,395	45,390	45,390
Received month	Qty recd																								
Jan'18	4																				1	1		2	
Feb'18	6																	2	1			3			
Mar'18	8														3	3	2								
Apr'18	0																								
May'18	3									3															
Jun'18	6											2	4												
Jul'18	7														2	2		3							
Aug'18	10						4				3			1	2										
Sep'18	1															1									
Oct'18	12						1			2			2	5	2										
Nov'18	9						3		2		2			2											
Dec'18	0																								

3.4 Sample Size Selection

The important parameter in conducting test is sample size and is determined as below; The Weibull distribution is chosen to represent the failures of the product. Since finding out the sample size for reliability testing using the Weibull model is highly complex, the exponential distribution is considered for the approximation of the sample. The sample size is calculated as below [7].

$$N = \frac{\chi^2_{(2r+2),\gamma}}{2F_{(t_n)}} \text{ In which } \qquad F_{(t_n)} = 1 - e^{-\lambda_R t_n} \text{ and} \tag{1}$$

$$t_n = t_s \times A_F \text{ Where} \tag{1a}$$

λ_R = the specified average failure rate

t_n = the test time under normal operating conditions

A_F = the acceleration factor between test and normal use conditions (if normal test A_F =1)

t_s = the accelerated test duration

γ = the confidence coefficient

f_r = the failure demonstration number

$\chi_{(2r+2),\gamma}$ Denote the γ cutoff point of the chi-squared distribution with (2 f_r +2) degrees of freedom. Degrees of freedom indicates the amount of independence in a data set.

Number of samples $N = \frac{\chi^2_{(0+2),0.8}}{2 \times 0.05} = \frac{\chi^2_{2,0.8}}{0.1} = \frac{0.4748}{0.1} = 5$

3.5 Execution of Test to Collect Failure Data of

Referring to table 4, which describes chances of failures under different test conditions, we could understand that dynamic tests are more severe on the product when compared to all other tests. Warranty data also reveals the same failure mode. Hence it is decided to select dynamic test as a representative of the entire test specification. Though we already categorized the product into 5 subassemblies, a test has been conducted as a whole product & failures have been recorded with respect to subassembly classification. The sample size for each test is 5. Since there is a practical constraint of monitoring the exact product failure duration, interval censored type of data was collected. To spread the chance of variation in this process, the inspection interval also kept dissimilar for each subassembly.

Table 5: Failure Data from Test Bench

Sub-Assembly	Sample Number	Failure / Suspension Duration (Intervals) in Hours In Between		Fail/ Suspension
Sub-system A	1	65	70	S
	2	43	47	F
	3	50	53	F
	4	41	44	F
	5	57	60	S
Sub-system B	1	62	65	S
	2	51	56	F
	3	58	65	S
	4	65	70	S
	5	60	65	S
Sub-system C	1	65	70	S
	2	63	70	S
	3	68	70	S
	4	62	68	S
	5	63	69	S
Sub-system D	1	67	69	S
	2	65	68	S
	3	65	69	F
	4	72	75	S
	5	65	69	F
Sub-system E	1	68	74	S
	2	55	60	F
	3	63	67	S
	4	65	71	S
	5	54	56	F

3.6 Average Distance Covered by a Vehicle Per Day

To calculate the duration covered before failure, data available in months needs to be converted to kilometers. This can be carried out if we have the data about the average distance covered by a vehicle per day. To capture the data, selected three two-wheeler dealers & collected data for average distance covered by a vehicle from their sales & service record. This comes around 32.5 kms / day. Detailed chart of the collected data is attached as Annexure-1

4. PROCESSING OF COLLECTED DATA

The data collected & presented in the previous section are raw data & needs to be processed to arrive the life / Reliability of the field. [8] Processing of data involves the following steps;

5.1 Arrive conversion factor for the test duration

5.2 Convert test failure duration available in hours to kilometers

5.3 Convert warranty failure duration available in days to kilometers

4.1 Arrive Conversion Factor for the Test Duration

The failure data captured from the test bench is in hours. The organization offers a warranty of 1 year. To predict the reliability at the end of one year, this data needs to be converted into kilometers. Data collected to arrive the average distance covered by a vehicle in a day. This has been collected from authorised two-wheeler agency. The average distance

covered by a vehicle in the field is 32.5 kms per day. That means warranty period is 365 days x 32.5 kms, which gives a value of 11862.5, rounded off to 11863 kms. Considering this assumption as a base for conversion, the following chart was formulated;

Table 6: Conversion Factor For Each Test

Classification of Tests	Nature of Test	Test Duration	Conversion Factor (Kilometers Equivalent to 1 Hour of Test Duration) 11,863 kms /Test Duration
Environmental	Corrosion resistance	50 Hours	238
	High temperature	192 hours	62
	Low temperature	192 hours	62
	Humidity	192 hours	62
	Thermal shock	100 cycles	118
Dynamic	Vibration - Sine	8 hours	1483
	Vibration - Random	60 hours	198
	Bump	1000 bumps	12
Endurance	Leak test	100 cycles	119
	Operational durability test	100,000 cycles	0.12

Note: Conversion factor rounded off to next digit.

4.2 Conversion of Test Failure Data Into kilometers

The above conversion factor is used to convert test failure duration available in hours to kilometers & is tabulated below;

Table 7: Test Results Converted into Kilometers

Sub-Assembly	Sample Number	Failure / Suspension Duration (Intervals) in Hours		Failure / Suspension Duration (Intervals) in Kilometers		Fail / Suspension
		In Between		In Between		
Sub-system A	1	65	70	12870	13860	S
	2	65	68	12870	13464	S
	3	61	63	12078	12474	F
	4	67	69	13266	13662	S
	5	57	60	11286	11880	S
Sub-system B	1	62	65	12276	12870	S
	2	58	62	11484	12276	F
	3	63	65	12474	12870	S
	4	65	70	12870	13860	S
	5	60	65	11880	12870	S
Sub-system C	1	65	70	12870	13860	S
	2	63	70	12474	13860	S
	3	68	70	13464	13860	S
	4	62	68	12276	13464	S
	5	63	69	12474	13662	S
Sub-system D	1	67	69	13266	13662	S
	2	65	68	12870	13464	S
	3	65	69	12870	13662	F
	4	72	75	14256	14850	S

	5	65	69	12870	13662	F
Sub-system E	1	68	74	13464	14652	S
	2	58	60	11484	11880	F
	3	69	72	13662	14256	S
	4	65	71	12870	14058	S
	5	61	65	12078	12870	F

4.3 Processing of Warranty Failure Data

Warranty failures consolidated in table 4, need to be processed further to calculate the reliability of the product in the field. Distance covered before failure or suspension is calculated using the same conversion rate of 32.5 kms / day. Failure month is not directly considered for calculation, instead it has been considered as the sample failed between two months. For example, if a rejection is received within a month of supply, it has been considered as the failure happened between 0 to one month which is equivalent of 0 to 1008 kms (31 days x 32.5 kms). Similarly, all the data points converted & are tabulated as below;

Table 8: Field Failures Converted to Kilometers

Mfg Month	Qty Supplied	Failure / Suspension	Qty Failed	Duration in Intervals (Months)		Duration in Intervals (Kilometers)	
				Start	End	Start	End
Feb-07	45,390	F	2	10	11	9,750	10,725
		S	45,388	23	23	22,425	22,425
Mar-07	48,395	S	48,395	22	22	21,450	21,450
Apr-07	40,400	F	1	8	9	7,800	8,775
		F	3	9	10	8,775	9,750
		S	40,396	20	20	19,500	19,500
May-07	57,692	F	1	7	8	6,825	7,800
		S	57,691	19	19	18,525	18,525
Jun-07	30,129	S	30,129	18	18	17,550	17,550
Jul-07	54,925	F	1	6	7	5,850	6,825
		S	54,924	17	17	16,575	16,575
Aug-07	39,400	F	2	6	7	5,850	6,825
		F	3	10	11	9,750	10,725
		S	39,395	16	16	15,600	15,600
Sep-07	45,380	F	2	5	6	4,875	5,850
		S	45,378	15	15	14,625	14,625
Oct-07	34,098	F	3	4	5	3,900	4,875
		F	2	8	9	7,800	8,775
		F	1	10	11	9,750	10,725
		S	34,090	14	14	13,650	13,650
Nov-07	62,098	F	3	3	4	2,925	3,900
		F	2	7	8	6,825	7,800
		F	2	8	9	7,800	8,775
		F	2	10	11	9,750	10,725
		S	62,089	13	13	12,675	12,675
Dec-07	40,986	F	1	7	8	6,825	7,800
		F	5	9	10	8,775	9,750
		F	2	10	11	9,750	10,725
		S	40,978	12	12	11,700	11,700
Jan-08	53,295	F	4	4	5	3,900	4,875
		F	2	8	9	7,800	8,775
		S	53,286	11	11	10,725	10,725

Feb-08	43,679	F	2	2	3	1,950	2,925
		S	43,677	10	10	9,750	9,750
Mar-08	48,930	F	3	4	5	3,900	4,875
		F	2	7	8	6,825	7,800
		S	48,925	9	9	8,775	8,775
Apr-08	54,878	F	3	0	1	0	975
		F	2	5	6	4,875	5,850
		S	54,873	8	8	7,800	7,800
May-08	42,875	F	2	5	6	4,875	5,850
		S	42,873	7	7	6,825	6,825
Jun-08	43,972	S	43,972	6	6	5,850	5,850
Jul-08	54,925	F	4	0	1	0	975
		F	1	2	3	1,950	2,925
		F	3	3	4	2,925	3,900
		S	54,917	5	5	4,875	4,875

5. ANALYSIS AND INTERPRETATION OF DATA

5.1 Choice of Techniques

The failure data obtained from lab tests & field returns are used to predict the reliability of the components. Two-parameter Weibull distribution is used to approximate the failures of components / subassemblies. To predict the reliability of the product, Weibull parameters eta & beta has to be calculated. From the failure data of the components, the median ranking (MR %) is calculated [9]. The above two values failure time & MR are used to find the reliability of the subassembly. There are three methods available to calculate the Weibull parameters;

- Weibull plotting
- Regression Analysis: X on Y
- Maximum Likelihood Analysis

Weibull plotting is a log-log plot of the probability of failure versus age for a product or subassemblies. However, the basic constraint in this method is the least accuracy and complication of calculation when multiple data points are involved. Moreover, we cannot handle grouped data in this methodology of plotting. Hence, this paper aims at calculating the Weibull parameters using regression and Maximum likelihood estimation. Since we have censored data, the data has to convert into complete data or uncensored data. The analysis of censored data as follows

5.1.1 Analysis of Right Suspended Data

Calculating the Weibull parameters for censoring with interval data is a complicated one. To better illustrate the methodology, consider the following example shown in Table 9 where five items are tested resulting in three failures and two suspensions.

Table 9: An Example Failure Data For Censored Analysis

Sample Number	Failed/Suspended		Life of the Sample
	F/S	F/S Sequence	
1	F	F_1	8000
2	S	S_1	10000
3	F	F_2	12000
4	S	S_2	15000
5	F	F_3	20000

The methodology for plotting suspended items involves adjusting the rank positions and plotting the data based on new positions, determined by the location of the suspensions. The first item must be a failure, hence, it is assigned failure order number j = 1.[6] The actual failure order number (or position) of the second failure, F_2 is in doubt. It could S_1 be in either position 2 or in position 3. If S_1 was not withdrawn from the test at 10,000 hr it could have operated successfully past 12,000 hr, thus placing F_2in position 2. Alternatively, S_1could also have failed before 12,000 hr, thus placing F_2in position 3. In this case, this failure order number for F_2 will be some number between 2 and 3 [9]. To determine this number consider the following.

F_2 in Position 3	
1	2
F_1	F_1
S_1	S_1
F_2	F_2
S_2	F_3
F_3	S_2

It is possible to find the number of ways the second failure can occur in either order number 2 (position 2) or order number 3 (position 3). The possible ways are listed

F_2 in Position 2					
1	2	3	4	5	6
F_1	F_1	F_1	F_1	F_1	F_1
F_2	F_2	F_2	F_2	F_2	F_2
S_1	S_2	F_3	S_1	S_2	F_3
S_2	S_1	S_1	F_3	F_3	S_2
F_3	F_3	S_2	S_2	S_1	S_1

And

It can be seen that F_2can occur in the second position six ways and in the third position two ways. The most probable position is the mean of these possible ways, or the mean order number (MON) [7], given by

$$F_2 = MON_2 = \frac{(6\times2)+(2\times3)}{6+2} = 2.25$$

Using the same logic on the third failure, it can be located in position number 3, 4 and 5 as below;

F_3 in Position 3	
1	2
F_1	F_1
F_2	F_2
F_3	F_3
S_2	S_1
S_1	S_2

F3 in Position 4		
1	2	3
F_1	F_1	F_1
S_1	F_2	F_2
F_2	S_1	S_2
F_3	F_3	F_3
S_2	S_2	S_1

F_3 in Position 5		
1	2	3
F_1	F_1	F_1
S_1	F_2	F_2
F_2	S_1	S_2
S_2	S_2	S_1
F_3	F_3	F_3

Mean order number for the third failure, F_3 (Item 5) is,

$$MON_3 = \frac{(2\times 3)+(3\times 4)+(3\times 5)}{2+3+3} = 4.125$$

Once the mean order number for each failure is established, we obtain the median rank positions for these failures at their mean order number. Specifically, we obtain the median rank of the order numbers 1, 2.25 and 4.125 out of a sample size of 5, as given next.

$$\text{Median Rank Position=MR (\%)} = \frac{i-0.3}{N+0.4} \tag{2}$$

i=Position of failed sample

N= Total number of the sample failed.

Table 10: Complete Data from Censored Data

Plotting Positions For The Failure (Sample Size =5)			
Failure No.	**Failure Sequence**	**Mon**	**Median Rank Position**
1	F_1	1	0.13
2	F_2	2.25	0.36
3	F_3	4.125	0.71

Once the median rank values are obtained, either Weibull plotting or regression analysis (X on Y or Y on X) is used to find the reliability of the components. Regression analysis gives accurate result than plotting method.

5.2 Parameter Estimation using Rank Regression

Failure rate or hazard rate is given by[9]

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{3}$$

$$e^{-\left(\frac{t}{\eta}\right)^{\beta}} = 1 - F(t) \tag{4a}$$

Take log on both times

$$\ln[-\ln(1-F(t))] = \beta \ln t - \beta \ln \eta \tag{4b}$$

The general equation is given by

$$y = a + bx \tag{4c}$$

Relate equations 6.4 and 6.5 and the constants a, b given by

$$\begin{aligned} a &= -\beta \ln \eta \\ b &= \beta \\ y &= \ln[-\ln(1 - F(t))] \\ x &= \ln t \end{aligned} \tag{4d}$$

Table 11: Regression Analysis Parameters

Sample No	Time to Failure(t)	F(t) or MR	*X*	*Y*	*XY*	X^2
1	8000	0.13	8.98	- 1.97	-17.71	80.77
2	12000	0.36	9.39	- 0806	-7.57	88.22
3	20000	0.71	9.90	0.213	2.11	98.08
			$\sum X$ =28.28	$\sum Y$ =-2.563	$\sum XY$ =-23.18	$\sum X^2$ =267.07

5.3 Parameter Estimation using Maximum Likelihood Analysis

Regression analysis and plotting methods are only considering the failure time of the samples. If any change in the suspended data it will not affect the Weibull parameter values. So avoid this difficulty and to obtain the accurate result the maximum likelihood function is used. Here the failure time of both the suspended and failure samples are considered to find the Weibull parameters. Consider a distribution where *x* is a continuous random variable with *pdf* and *cdf*, [5] [9]

$$f(x; \theta_1, \theta_2, \ldots\ldots, \theta_k) \text{ and } F(x; \theta_1, \theta_2, \ldots\ldots, \theta_k) \tag{5}$$

Where $\theta_1, \theta_2, \ldots\ldots, \theta_k$ are the *K* unknown parameters which need to be estimated from *R* observed failures at $T_1, T_2, \ldots\ldots, T_R$ and *M* observed suspensions at $S_1, S_2, \ldots\ldots, S_M$ then the likelihood function for the Weibull model is formulated as follows,

$$L(\theta_1, \theta_2, \ldots., \theta_K / T_1, \ldots, T_R, S_1, \ldots, S_M) = \prod_{i=1}^{R} f(T_i; \theta_1, \theta_2, \ldots., \theta_K) \prod_{j=1}^{M} [1 - f(S_j; \theta_1, \theta_2, \ldots., \theta_K) \tag{6}$$

When using interval data, it is assumed that the failures occurred in an interval, i.e. in the interval from time A to time B where A < B. In the case of interval data, and given P interval observations, the likelihood function is modified by multiplying the likelihood function with an additional term Note that if only interval data are present, this term will represent the entire likelihood function for the MLE solution.

This log-likelihood function for two-parameter Weibull distribution censored data is given by [10]

$$\ln(\mathrm{L}) = \Lambda = \sum_{i=1}^{Fe} \mathrm{N}_{\mathrm{i}} \ln\left[\frac{\beta}{\eta}\left(\frac{\mathrm{T}_i}{\eta}\right)^{\beta-1} e^{-\left(\frac{\mathrm{T}_i}{r_i}\right)^{\beta}}\right] - \sum_{i=1}^{S} \mathrm{N}_{\mathrm{i}}^{'}\left(\frac{\mathrm{T}_i^{'}}{\eta}\right) + \sum_{i=1}^{FI} \mathrm{N}^{"}_{\mathrm{i}} \ln\left[(\exp-\left(\frac{\mathrm{T}_{\overline{L_i}}}{\eta}\right)^{\beta}) - (\exp-\left(\frac{\mathrm{T}_{\overline{R_i}}}{r_i}\right)^{\beta})\right] \tag{7}$$

Where,

F_e is the number of groups of times-to-failure data points,

N_i is the number of times-to-failure in the i^{th} time-to-failure data group,

β is the Weibull shape parameter

η is the Weibull scale parameter

T_i is the time of the i^{th} group of time-to-failure data,

S is the number of groups of suspension data points,

$N_i^{'}$ is the number of suspensions in i^{th} group of suspension data points,

$T_i^{'}$ is the time of the i^{th} suspension data group,

FI is the number of interval failure data groups,

$N_i^{''}$ is the number of intervals in i^{th} group of data intervals,

$T_{L_i}^{''}$ is the beginning of the i^{th} interval, and,

$T_{R_i}^{''}$ is the ending of the i^{th} interval.

The solution will be found by solving for a pair of parameters (β,η)) so that $\frac{\partial\Lambda}{\partial\beta}=0$ and $\frac{\partial\Lambda}{\partial\eta}=0$. [6]. It should be noted that other methods can also be used, such as direct maximization of the likelihood function, without having to compute the derivatives [10]

The Weibull parameters are estimated in the above two methods such as regression analysis and maximum likelihood analysis. To estimate Weibull parameters the Weibull++ software is used. The Weibull parameter for the above both analysis are given in the Table 12

Table 12: Weibull Parameter Values for Test Results

Subassembly Description	Regression Analysis		MLE	
	Beta (β)[Kilometers]	**eta (θ) (Kilometers)**	**Beta (β) [Kilometers]**	**eta (θ) (Kilometers)**
Sub-system A	57.8331	14,592	17.2222	15,600
Sub-system B	72.5054	14,359	47.9410	14,584
Sub-system C	97.6662	14,419	22.3770	15,268
Sub-system D	24.7402	14,605	22.6026	14,832
Sub-system E	27.0878	14,506	24.2214	14,752

5.4 Reliability of Sub-Assemblies using Test Results

The reliability of the components/subassemblies are estimated by using the Weibull reliability equation which is given by [11]

$$R(t) = e^{-\left(\frac{T}{\eta}\right)^{\beta}} \tag{8}$$

Table 13: Reliability after one Year (11,836 Kilometers)

Subassembly Description	Regression Based Analysis			MLE Based Analysis		
	Beta (β) (Kms)	eta (η) (Kms)	Reliability	Beta (β) (Kms)	eta (η) (Kms)	Reliability
Sub-system A	57.8331	14,592	0.9999	17.2222	15,600	0.9911
Sub-system B	72.5054	14,359	0.9999	47.9410	14,584	0.9999
Sub-system C	97.6662	14,419	1.0000	22.3770	15,268	0.9964
Sub-system D	24.7402	14,605	0.9942	22.6026	14,832	0.9936
Sub-system E	27.0878	14,506	0.9957	24.2214	14,752	0.9949

5.5 Reliability of Product Based on Test Results

To predict the overall reliability of the product, its system arrangements need to be considered. All the Components in the product are arranged in a simple series arrangement. So the Product reliability is a product of reliability of each components/subassemblies [12]

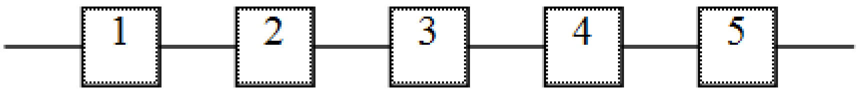

Figure 2: Simple Series System

A simple series system is shown in Figure 2 and system reliability can be determined by

$$R_s = R_1 \times R_2 \times R_3 \times R_4 \times R_5 \quad \text{For "n" number of components } R_s = \prod_{i=1}^{n} R_i \tag{9}$$

5.5.1 Based on Regression Analysis

R(1 year) = 0.9999 x 0.9999 x 1.0000 x 0.9942 x 0.9957 = **0.9897**

5.5.2 Based on Maximum Likelihood Estimation (MLE) analysis

R(1 year) = 0.9911 x 0.9999 x 0.9964 x 0.9936 x 0.9949 = **0.9761**

5.6Analysis of Field Failure Data

Reliability of product predicted based on the test bench data shows that the product will perform an intended function in the field for more than one year. But still, there are some failures in the field. Hence its necessary to calculate the reliability, based on warranty failures & to compare it with test bench results. The same methodology of regression-based analysis & MLE analysis was used to calculate the reliability [13]. Since the data points comprise of more complicated grouped, interval censored & suspended data, Weibull++ software used to calculate the Weibull parameters & is tabulated as follows;

5.6.1Weibull Parameters Based on Field Failure Data

Table 14: Weibull Parameter for Field Failure

Regression Analysis		MLE	
Beta (β) [Kilometers]	eta (η) (Kilometers)	Beta (β) [Kilometers]	eta (η) (Kilometers)
6.5907	17,628	6.2250	17,645

5.6.2Reliability Calculation Based on Field Failures Data

The reliability of the components/subassemblies are estimated by using the same Weibull reliability equation which is given by equation (8)

Table 15: Reliability for Field Failures

Analysis Method	Product Reliability after 1 Year Service in the Field
Regression	0.9291
MLE	0.9190

6. CONSOLIDATED RESULTS

6.1 Results Based on Test Results

Various tests have been conducted & its failure and suspension data were captured to predict the reliability of the product. As mentioned above, two analysis techniques & resulted values of reliability are listed below. Reliability of product after one year;

Using Regression analysis : 0.9897

Using MLE analysis : 0.9761

6.2 Results Based on Field Data

Field failure data captured for last one year & the corresponding manufacturing month of the failed product traced. Then the distance covered before failure was calculated. Failed quantity subtracted from total products supplied during respective month & remaining products considered as suspension, as those are still functioning in the field. This complete set of data used to calculate the reliability of products in the field.

The same methodology adopted for test bench failures was used to calculate reliability. Results are listed below;

Reliability of carburetor after serving one year in the field;

Using Regression analysis : 0.9291

Using MLE analysis : 0.9190

6.3 Summary of Results

Reliability of product after one year is calculated & is tabulated below;

Table 16: Summary of Results

Data Source / Analysis Method	Test Bench Failures	Field Failures
Regression	**0.9897**	**0.9291**
MLE	**0.9761**	**0.9190**

7. FINDINGS AND CONCLUSIONS

The following are the general observations and conclusions based on above-calculated values

- Comparatively, Dynamic tests are more severe on the product performance & having a strong impact on its failure
- Most of the times product fulfills the test specification requirements without any failure. (ie), the product passes the specified test duration
- Though the product follows a very good rejection level of less than 100 PPM in the field, its reliability is not up to the expectation.
- Reliability of product in the field is less than the reliability in test conditions. By this, we can clearly understand that the test conditions are not severe enough to simulate the field failure and there is a need to update Test procedure to improve the severity
- Considering the beta values, it can be seen that Product failure falls under the worn-out stage of the life cycle.
- Field failure suggests that the subassembly no. 3 is a weak link in the system & is having more impact on the poor reliability of the product.

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APPENDIX – I

The average distance covered by the vehicle per day is calculated using the data collected from authorized Two-wheeler sales and service agency and the same is tabulated below;

Table A1: Average Distance Covered by Vehicle Per Day

Vehicle (Sample) Number	Date of Sale			Total Kms Covered (Upto 1-2-2019)	Average Number of Days	32.5 Average Km / Day
	DATE	MONTH	YEAR			
1	16	1	2018	18975	380	49.9
2	22	12	2018	1254	39	32.2
3	14	2	2018	16786	352	47.7
4	30	11	2018	2717	61	44.5
5	25	7	2018	8098	188	43.1
6	4	12	2018	2100	57	36.8
7	19	6	2018	3531	225	15.7
8	10	12	2018	1020	51	20.0
9	26	8	2018	6352	157	40.5
10	29	8	2018	9873	154	64.1
11	20	12	2018	690	41	16.8
12	22	12	2018	684	39	17.5
13	22	12	2018	1123	39	28.8
14	22	12	2018	531	39	13.6
15	27	11	2018	670	64	10.5
16	10	2	2018	11200	356	31.5
17	30	6	2018	8762	214	40.9
18	22	12	2018	700	39	17.9
19	20	12	2018	828	41	20.2
20	23	9	2018	9200	129	71.3
21	13	6	2017	25639	596	43.0
22	16	1	2017	27965	745	37.5
23	1	6	2017	22730	608	37.4
24	9	1	2018	920	22	41.8
25	26	4	2017	20605	644	32.0
26	25	4	2017	15641	645	24.2
27	26	2	2017	30746	705	43.6
28	24	9	2018	1320	128	10.3
29	10	12	2018	1320	51	25.9
30	27	8	2018	4887	156	31.3
31	26	2	2017	44220	705	62.7
32	31	8	2015	49324	1,247	39.6
33	29	8	2018	8200	154	53.2
34	14	11	2018	2466	77	32.0
35	29	10	2018	4986	93	53.6
36	10	12	2018	1236	51	24.2
37	28	5	2017	8200	611	13.4
38	22	12	2018	423	39	10.8
39	9	1	2018	1261	22	57.3
40	9	6	2018	5501	235	23.4
41	25	10	2018	5426	97	55.9
42	5	11	2018	3452	86	40.1
43	20	2	2017	7700	711	10.8
44	6	5	2017	30972	633	48.9
45	27	6	2017	24999	582	43.0
46	24	1	2018	10401	372	28.0

Table A1: Contd.,

47	9	10	2018	4563	113	40.4
48	16	2	2017	24902	715	34.8
49	20	10	2018	3500	102	34.3
50	28	11	2018	2794	63	44.3
51	21	3	2018	7314	314	23.3
52	31	3	2018	15654	304	51.5
53	26	12	2017	10491	400	26.2
54	6	10	2018	2691	116	23.2
55	24	11	2018	6692	67	99.9
56	20	12	2018	1000	41	24.4
57	21	1	2016	38064	1,105	34.4
58	22	12	2018	771	39	19.8
59	21	3	2016	15054	1,044	14.4
60	22	12	2018	770	39	19.7
61	22	12	2018	762	39	19.5
62	4	1	2018	657	27	24.3
63	19	11	2018	2547	72	35.4
64	20	1	2018	11419	376	30.4
65	10	12	2018	977	51	19.2
66	28	11	2018	3288	63	52.2
67	4	12	2018	420	57	7.4
68	3	10	2018	2186	119	18.4
69	20	2	2018	6834	346	19.8
70	28	8	2018	4934	155	31.8
71	30	5	2018	8271	244	33.9
72	20	12	2018	1200	41	29.3
73	11	1	2018	400	20	20.0
74	20	12	2018	667	41	16.3
75	7	2	2018	7417	359	20.7
76	10	1	2018	16982	386	44.0
77	22	10	2018	3464	100	34.6
78	5	9	2018	8790	147	59.8
79	13	6	2017	11978	596	20.1
80	5	11	2018	2134	86	24.8
81	28	11	2018	2368	63	37.6
82	16	1	2018	18902	380	49.7
83	27	11	2018	1228	64	19.2
84	28	11	2018	2763	63	43.9
85	26	4	2017	25402	644	39.4
86	3	10	2018	4699	119	39.5
87	7	2	2018	7406	359	20.6
88	23	1	2018	215	8	26.9
89	24	5	2017	15856	615	25.8
90	7	11	2018	1861	84	22.2
91	22	12	2018	743	39	19.1
92	16	4	2018	14352	289	49.7
93	21	11	2018	2709	70	38.7
94	16	7	2018	6767	197	34.4
95	24	12	2018	154	37	4.2
96	7	11	2018	1400	84	16.7
97	20	12	2018	775	41	18.9
98	22	12	2018	727	39	18.6
99	3	3	2018	18965	332	57.1
100	27	3	2018	9451	308	30.7